Change Detection in Stockholm between 1986 and 2006 using SPOT Multispectral and Panchromatic Data

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Abstract

With an increasing urban population in Sweden, expecting to reach 90% by 2050 (UN World Urbanization prospects, The 2011 Revision), this high level of urban population put pressure on functioning infrastructure, sufficient housing and need to monitor the environmental effects such as pollution and the effects of land use change. Stockholm County currently holds 22% of the population and accounts for nearly half of the urban growth in Sweden (Svensk Handelskammare).

Previous research on change detection using remote sensing cover the use of data sets from optical sensors, infrared spectrum, radar data and the use of additional derived data sets such as indices and texture measure (implemented on pixel or feature level). There is not yet any consensus regarding which change detection methods that is superior to others. Comparative studies often only test a few algorithms on one particular data set. Change detection of Stockholm urban area has not been well investigated in previous literature.

This thesis is focused on a change detection analysis of Stockholm area between 1986 and 2006 using remote sensing data fusion. The data set used is SPOT-1 HRV XS data at 20m resolution from 1986, SPOT-1 HRV Panchromatic data at 10m resolution from 1987 and SPOT-5 HRG XS data of 10m resolution from 2006.

The first challenge was to fuse the multispectral and panchromatic images from 1986 and 1987 to inject the details of the 10m panchromatic image into the 20m multispectral so that the resulting images will have similar spatial details as the 2006 images. This was done by wavelet transform. Haar, Daubechies, Coiflet and Biorthogonal wavelet families were tested to find the optimal fusion and the corresponding parameters. The results showed that the Daubechies, Coiflet and Biorthogonal families did not differ significantly and that for this data set and analysis purpose more than one wavelet family fusion results showed satisfactory results. The correlation coefficient for these three families was all over 0.96 at decomposition level two.

Then change detection was performed using change vector analysis (CVA) and a supervised non-parametric classifier. A comparison is made between two inputs: one using only spectral information and the other adding textural information to the spectral information. The
change detection analysis was undertaken in three steps: calculating texture measures from the original images, calculating change magnitude using Change Vector Analysis (CVA) and classifying change from no-change using Support Vector Machine (SVM).

Three GLCM texture measures were chosen: Homogeneity, Mean and Entropy in the change detection analysis. These, as well as the spectral information, were input for change vector magnitude. Then SVM is used to classify changed pixels from no-change pixels. Two change results were obtained, the first using only spectral information, and the other using both spectral and textural information.

The overall accuracy using only spectral information was rather high at 87, 86%. But the visual inspections indicate that using only spectral change magnitude is not sufficient for a good change detection result because there is an apparent overestimation of change. When adding the textural information the overall accuracy increase drastically to 97,01%, although at visual inspection there seem to be an underestimation of change. Because of the high overall accuracy an independent validation was made causing the overall accuracy and kappa to decrease. Change detection using only multispectral data got an overall accuracy of 76, 12% and kappa coefficient 0,53. For change detection result with added texture measures the overall accuracy became 85,80% and 0,72. The results further confirm the general advantages using texture measure although the independent evaluation resulted in a lower accuracy than the author’s evaluations.
1. Introduction

More than 50% of the world’s population is already living in urban areas. Globally, the population living in urban areas is predicted to increase from 3.6 billion in 2011 to 6.3 billion by 2050. Although there were 23 megacities in the world with at least 10 million inhabitants they only constitute about 10% of the urban population. Half of the urban population live and will continue to do so in cities with less than 500,000 people and about 10% of the urban population lives in cities with 500,000 to 1 million people (UN World Urbanization prospects, The 2011 Revision: Highlights). In Sweden 65.7% of the population lived in urban areas in 1950. In 1985 it had increased to 83.1% and the forecast for 2050 is 90.0% (UN World Urbanization prospects, The 2011 Revision). Stockholm County is not one of the largest urban areas on an international level but experience one of the highest growth rates in Europe since 2000. Urbanization has both positive and negative effects. While it may be beneficial from an economic market perspective and create place for innovation, research and culture, an increased population also put pressure on the infrastructure, schools and care. It can create housing deficiency, traffic congestion problems and air pollution as well as other environmental problems (Stockholm Handelskammare, 2013).

Remote sensing is a constantly growing area of research and the availability of data is increasing. There are panchromatic, multispectral, hyperspectral and radar sensors and spatial resolution has improved rapidly during the last decades. Applications for the remote sensing area are numerous such as forest monitoring, marine applications, urban and environmental change to name a few Lu et al (2004). The benefits of remote sensing analysis cover subject fields from city planning to local as well as global environmental studies.

Since Stockholm urban area stretch over several municipalities it can be beneficial to have an overview of development over the whole area. Satellite images data does not consider any administrative boundaries which is strength of remote sensing. Another advantage is the large swath width of the images. One image acquired satellite can be enough to cover a study region but it is sensor and application dependent.

With revisiting satellites passing and recording the same areas on a given intervals, in addition to long term satellite missions over decades, it is possible to make time analysis to monitor change using data from same or similar sensors. Although the spatial resolution has
improved since the first satellite missions, pansharpening or data fusion make it possible to combine older multispectral data of low spatial resolution with panchromatic data with higher resolution in order to match the newer data sets. SPOT has provided data since 1986 which make it possible to use for change detection over a longer time. The resolution is relatively high even for the older data 20m MS and when using image fusion using panchromatic band it is possible to have 10 resolution. Because it a system that is designed for long term continuity payloads within the program are similar.

To compare possible data sources that has provided image for a longer period of time such as Landsat 4 and 5 (1982 and 1984) TM and cover large swath area 185km but only have a resolution of 30m. Landsat 7 (1999) ETM+ also registers 15m panchromatic. Jensen (2005, pp. 47-62). Since panchromatic Landsat information is not available before ETM+ sensor it is not possible to perform data fusion with data before this date. There are also several satellites (Ikonos, Quickbird) offering high resolution data (sub meter for panchromatic and a few meters for multispectral) but the time span of supplying data is not more than about 10 years. Stockholm is growing and densifying but due to political processes of planning the actual time for changing plans and land use or building houses is long. For this reason the time interval of monitoring Stockholm will not be very meaningful over a too short interval.

Another important aspect to consider is the cost of the products. Landsat data has been made free of cost. And SPOT data has considerably lower prices than the very high resolution data products. Therefor it can be considered as a good compromise of cost and spatial resolution to choose SPOT data before Landsat in addition to the timeframe of availability of data dating back to 1986 compared to the satellite images of higher resolution.

Low resolution data for change detection in an urban environment might not be sufficient if the change has not occurred in larger coherent areas. A spatial resolution of 10m can make it possible to detect the objects on the ground such as large buildings. This is valuable because an urban environment comprises smaller objects than more homogenous land covers such as forest, crops or water.

Change detection using SPOT data has mainly been performed using the panchromatic band and not using the multispectral bands or only using selected bands. Combining multispectral and panchromatic data from Landsat and SPOT has also been tested Zhang, Y. (2001), Deng
et al (2009). The use of Landsat data for optical change detection seems to be further investigated than SPOT, possibly because due to cost reasons. By using only panchromatic data or not including all bands such as NDVI index (red and NIR band) leads to not using the full information of the sensors i.e. not making use of all multispectral band information and the high spatial resolution of the panchromatic band.

In addition to the information given by the original data sets, several indications that adding texture measures as input to the analysis can improve classification and/or change detection results. This has been reported in previous research using SPOT and other data sets He et al., (2011), Zhang, Y,( 2001). NDVI as input for image differencing and texture segmentation for has also been investigated Wang & Zhao (2009). CVA as a method for deriving a change variable has been tested using Landsat data but is not for SPOT in urban change detection. A problem of change detection seems to be the step of extracting the change and obtaining a correct detection. This is usually performed by thresholding based on empirical knowledge or statistical methods. Other methods include supervised classification of the change image.

While the urbanization monitoring using remote sensing is great, very little has been published on change detection of Stockholm apart from urban land cover change detection by Kolehmainen and Ban (2008) and Furberg and Ban (2013). Therefore, the overall objectives are to investigate data fusion of panchromatic and multispectral data using wavelet transform and to conduct a change detection analysis in the Stockholm area between 1986 and 2006 using SPOT data at 10m resolution using a supervised change detection method.

The specific objectives of this research are:

- Compare wavelet families and their fusion results for fusion of multispectral and panchromatic images of different spatial resolution
- To test the effectiveness of change vector analysis using change magnitude as a step in change detection
- Use and evaluate SVM classifier and different kernels for classification of change images
• To compare the effectiveness of only spectral information and adding textural information to the change detection analysis

The outline of this paper is first a literature review of change detection methods and textures and indices. It will include some of the research up until now and different approaches regarding change detection. It is followed by a methodology chapter describing the chosen method for this thesis. The results are presented together with a discussion. Finally some conclusions are drawn and some suggestions are made for future research.
2. Literature review

2.1 Data fusion

The purpose of image fusion is to combine two or more images into one image to gain additional information that can be extracted visually or to be processed further. Advantages of image fusion are not restricted to the remote sensing application area; it is used in other fields such as medicine and surveillance. The process should reduce redundancy to smallest amount possible and task relevant information should be made as large as possible. Image fusion algorithms can be grouped as pixel, feature (segmented regions) or symbolic level. On the pixel level multiresolution analysis is a common technique. Early fusion techniques entail Laplacian pyramid techniques; pyramid schemes and later discrete wavelet transform (DWT) Goshtasby & Nikolov (2007). Sensors of today’s satellites for example Quickbird and SPOT supply imagery with diverse characteristics. Panchromatic image has high spatial resolution whereas multispectral image contain high spectral information content. This means potential for making use of both the high spatial and spectral information within one single image Shi et al. (2005). Fusion of images from optical and SAR sensor are also proven advantageous than a single sensor (Ban et al., 2010; Ban and Jacob, 2013).

For many remote sensing applications there is a need for both high spectral and spatial resolution in particular when the analysis is large scale. The reasons why we need good fusion results vary depending on application but better interpretation, higher classification accuracy and visualization are a few purposes. There are practical reasons as to why not imagery that combine these two characteristics high spatial and high spectral is gathered with one sensor. For a Pan sensor to receive equal amount of energy can be smaller than a MS sensor since it collects a wider range of wavelengths and resolution can be higher. Also the amount of data would increase a lot if MS sensors were to be high resolution and satellites storage capacity as well as transmitting the data can become an issue Zhang, Y. (2004).

Some of the popular techniques are IHS, PCA, arithmetic combination and wavelet based fusion. IHS is the conversion of an image from RGB into IHS space. The Intensity component is replaced by the panchromatic image due to its resemblance and the new IHS image undergoes a reversed transformation back to RGB space. In PCA fusion the low resolution
MS image is transformed into uncorrelated components. One uses the panchromatic image to replace the first component of the multispectral bands before a reversed transform. As an example of the arithmetic approaches example the Brovey transform entail multiplication of each multispectral band with the panchromatic of higher resolution. The products are then divided by the sum of multispectral bands. Wavelet based fusion is the decomposition of the panchromatic band to several low resolution images with coefficients containing spatial detail. At the right resolution level the MS image replace the panchromatic low resolution image on band basis and the details are fused in each band using a reverse transform Zhang, Y. (2004).

During the years attention has been paid to deal with improving the quality of fused images and to minimize the effects of colour distortion. Quality of the fusion is often affected by the analysts experience and the original data set. To alleviate colour distortion problems different kinds of stretching have been proposed for HIS and PCA and variations of wavelet fusion approaches Zhang, Y. (2004). Newer satellites like IKONOS, QuickBird and Landsat 7 provide panchromatic images with a different spectral range than older missions such as SPOT that lay within the visible range. The newer panchromatic images also include part of the near infrared spectrum which changes the gray levels. This causes difficulties when applying fusion techniques developed and adapted for data acquired from older satellites. To replace Intensity in IHS, first principal component and injecting detail in wavelet with panchromatic image containing near infrared will cause colour distortion Zhang, Y. (2004).

Comparison to other previous merger techniques was performed by Yocky (1995) He used DWT for fusion comparing Haar and Daubechies families to HIS using coefficient replacement and found that Daubechies wavelets had lowest RMS errors. Garguet-Duport et al. (1996) also made a comparison of change in spectral characteristics in HIS, P + XS and biorthogonal wavelet fusion methods of panchromatic and multispectral SPOT data. The wavelet method proved to maintain the most radiometric information. Núñez el al (1997) successfully performed fusion of panchromatic and multispectral data with an additive scheme using discrete wavelet transform, “á trous”, on Landsat TM and SPOT data. In a detailed comparison of standard fusion schemes (HIS, PCA), Wavelet schemes (substitutive, additive and weighted) and Hybrid methods Amolins el al (2007) argues that simple wavelet schemes perform better than the standard HIS and PCA fusion techniques. Models with
weighted coefficients generally achieved better results than the other simple wavelet schemes but also had an increase in computational complexity. The hybrid models showed best results.

A comparison of Intensity Hue Saturation (IHS) Transform, PCA, DWT and Discrete Wavelet Frame Transform (DWFT) was performed by Li, Kwok and Wang (2002) using Landsat TM and SPOT data. Radiometry was changed after fusion in both HIS and PCA fusion. DWFT acquired best statistics in case of spectral difference and spatial correlation. DWFT also performed better than DWT when images were manually shifted. One main advantage with DTWT compared to DWT is that it does not use downsampling and therefore is not shift variant which is useful when registration is inadequate.

An interesting development was performed by Shi et al. (2005) using a multi band wavelet based image fusion and compared to the two band wavelet method and HIS fusion as well as applying various assessment techniques. The results showed that a four band approached performed better than two band or HIS method.

A general multiscale decomposition framework was studied by Zhang & Blum (1999) where Laplacian pyramid transformation (LPT), DWT and DWF were evaluated and management of the coefficients investigated. Comparisons of activity measurements, coefficient grouping methods, coefficient combining methods and consistency verification methods were also made. Results indicate that DWT and DWF are preferred over LPT, region based activity level measurement and multiscale grouping performed best. The combining methods showed similar result and region based activity consistency verification did better than the other methods.

Pajares & Manuel de la Cruz (2004) gave a tutorial on wavelet fusion theory and compared coefficient merging techniques. Several wavelet families were also evaluated: Daubechies, Coiflet, Symlets, Biorthogonal, Reverse biorthogonal, Mexican hat and Morlet of several filter sizes and levels and the best results compared to other methods. Best correlation of original and synthesized images was Local Mean Matching (LMM) and Local Mean and Variance Matching (LMVM) followed by Biorthogonal 2, 2, Coiflet 1 and Daubechies 4 wavelets. The authors also note a decrease in performance as filter size grows and lower performance of increasing number of levels.
Alparone et al (2007) presented results from the IEEE GRS-S Pansharpening Competition. Two multiresolution analysis algorithms outperformed the other, mainly component-substitution based, algorithms. The common denominators of the best algorithms were the consideration of the sensors modulation transfer functions and adaptive detail injection.

Recently new transforms have emerged. Li, Yang and Hu (2011) tested the performance of Discrete Wavelet, Stationary Wavelet (SWT), Dual-Tree Complex Wavelet (DTCWT), Curvelet (CVT), Contourlet (CT) and Nonsubsampled Contourlet Transform (NSCT) for multi focus, infrared-visible and medical application areas. They considered decomposition levels and found that more than four levels introduced undesired effects. Of the DWT families considered (Daubechies, Symlets, Coiflets, Biorthogonal and Reverse Biorthogonal) Daubechies and Biorthogonal gave good results, in particular with short filters. For Infrared visible application Daubechies gave best results for tree out of five evaluation metrics. Overall shift invariant transforms perform better than shift variant but the complexity and larger need of memory also need to be considered.

Zhang, Y. (2008) addressed the trouble of choosing a reliable quality assessment. Two approaches were discussed. The qualitative approach of visual examination of color distortion after fusing MS and pan data and improved spatial detail of the fusion image compared to the pan image which usually involves subjective opinion. To be able to make a consistent evaluation it important to keep visualization circumstances equal or false discrepancies between results might be incorrectly found. The quantitative evaluation approach requires indicators to judge the similarity of original and fused image. Some common indicators are Mean bias, Variance difference, correlation coefficient, spectral angle mapper, relative dimensionless global error, and Q4 quality index. Yet there is no common standard for quantitative approach for image fusion evaluation. Their tests of the different indicators show large variation in describing image likeness when used on altered images (shifted and/or stretched) but with same qualities for remote sensing applications and deemed not sufficient as evaluation measurements.
2.2 Change detection

2.2.1 Pixel-based change detection

The purpose of change detection is finding differences of objects over time. Change detection is used for numerous applications such as land-use and land-cover change, forest change, fire detection, desertification etc. Data from different sensors with various spatial and spectral resolutions can be used depending on availability and purpose. A comprehensive review of early change detection methods (grouped in algebra (image differencing, image regression, image ratioing, CVA, etc.), transformation (PCA, Tasselled cap, Chi Square, etc.) , classification, advanced models, GIS approaches, visual analysis and other approaches) can be found in Lu, D et al (2004) along with their application area, advantages and disadvantages. They conclude that no algorithm is suitable for all applications but have their own benefits.

Coppin et al (2004) divide ecosystem change detection into two categories: bi temporal and temporal trajectory analysis, where the first use two images of the same period but different years and the second is continuous over time. For bi-temporal analysis the acquisition dates are of great importance. This is to minimize the effects of seasonal differences of vegetation and sun angle. For this reason anniversary dates are preferred. Also local precipitation and temperature difference can cause problems for ecosystem application.

Data preprocessing aims to reduce the effects that can cause false change results. Such noise can be caused by differences of solar azimuth angle sensor, calibration deviation, and scattering and absorption differences due to atmospheric conditions. Error removal, noise reduction and masking are important preprocessing steps for a single remotely sensed image. For multi-date images pre-processing can also include atmospheric normalization, registration, geometric correction and mosaicking. A supplementary step before change detection can be filtering such as edge-enhancer or smoothing filters but the opinions on the efficiency vary. For bi-temporal change detection image registration and radiometric correction are the most important requirements. Both mis-registration and improper normalization can be a source of false change results Coppin et al (2004).
The choice of a suitable change detection method is not an easy task. There are a large variety of algorithms and combinations. Normally there are two general steps of the analysis, the derivation of a change variable and either a thresholding or classification step. Some of the common methods are:

Post classification comparison or delta classification procedure includes separate classification of multi-date imagery either pixel or segmentation based. A change matrix can be obtained by comparing land cover classes and change classes can be labeled. This change matrix provides full to-from information. Another advantage is that by separate classifications, radiometric discrepancies are minimized. A disadvantage is that the final accuracy is dependent on the separate accuracies of the two classifications Coppin et al (2004).

Univariate image differencing is the subtraction of an image of one date to image of the other date. This can be done for an original image or for example a computed index (such as NDVI). The resulting values of zero denote no change whereas negative and positive values represent change Coppin et al (2004). An issue with this method is the inability to separate difference values of the same magnitude, although they might have been calculated from very different original value Singh (1989). Image ratioing is when images are ratioed on pixel basis. No change is represented by a value of one. Changed pixels will have higher or lower values. A limitation is the non-Gaussian distribution when considering thresholding Coppin et al (2004).

Change vector analysis produces change magnitude and change direction as output of the input image. An advantage is that the method is not limited to analysis of single bands but make use of the dimensionality of the data Coppin et al (2004).

Image regression is the assumption that pixels of two dates will be linearly related. A fit through a mathematical model is computed using regression. Changed pixels are determined by the size of the residuals Coppin et al (2004).

Principal Component Analysis reduces the information by transforming to a few principal components holding the most variance of the images Singh (1989). Principal Component Analysis (PCA) and unsupervised classification was performed by Deng et al. (2009) of
Hangzhou, China. They used SPOT-5 XS 10m and Landsat 7 Enhanced Thematic Mapper (ETM) PAN 15 m data to detect land use change. A maximum likelihood classification was performed for identification of 10 classes. Yousif and Ban (2013) used PCA to reduce dimensionality in their change detection of urban areas using multitemporal SAR data.

Composite analysis, Bi temporal linear data transformation, Multi temporal Spectral mixture analysis, Multidimensional temporal feature space analysis, Hybrid Coppin et al. (2004) Direct Multidate classification, background subtraction Singh (1989) are other approaches to change detection.

After change has been computed, several methods require thresholding to separate the changed pixels from unchanged pixels. A limit, threshold value, is calculated or chosen based on statistical or empirical grounds. If several thresholds are sought for density slicing can be used Singh (1989). Wu, De Pauw and Zucca (2008) grouped change detection algorithms into two groups: thresholding and non thresholding. The first include differencing, rationing, regression, CVA and cross correlation. The other concern delta data change detection and post classification methods. Even though post classification are associated with the possibility of large errors due to misregistration and poor classification the better results can be achieved than before as new classifier and more advanced technology and techniques emerge. Chen & Wang (2010) also mention that problems associated with radiometric calibration of two dates can be minimized using post classification change detection.

Radke et al. (2005) attended to the issue of ‘significant change’ between the images as opposed to differences caused by sensors, lighting circumstances or atmospheric conditions. They reviewed several methods including pre-processing methods, simple differencing, significance and hypothesis test, predictive models, shading models. Ridd and Liu (1998) applied four change detection algorithms, image differencing, image regression, tasselled cap transformation and a chi square transformation on Landsat TM imagery. A comparison of accuracy in detecting change and capacity of detecting type of change for urban application was performed showing regression and image differencing performed similarly effectiveness in detection using visible bands and differencing with band two performed well for urban change. Their conclusion however, was that no algorithm or band change image could prove consistently better.
Martínez, L et al (2007) used SPOT 5 panchromatic data in Catalunya are to find urban change by manually extracting change from RGB display of two date panchromatic images. The change is verified by a third image and the process was repeated with the second and third date image. They report trouble with specular reflection in industrial areas causing false change and additionally mention acquisition geometry of tall objects in SPOT data and variation of vegetation as problematic.

Martin, L.R.G & Howarth, F.J. (1989) used multispectral SPOT data to compare visual analysis and supervised maximum likelihood classification of two images and multidate images (band XS2) in the greater Toronto metropolitan area to detect rural to urban change. Best change accuracy was 60% with the multidate supervised classification. They discuss that the SPOT analysis does not obtain higher accuracies than Landsat MSS due to spectral variability of the higher resolution and that the number of edge pixels increase. They point out that the detail level of classification effect the accuracy greatly and that a change/no change classification would result in 90%.

R.D Johnson and E.S. Kasischke (1998) used CVA to detect change near Ann Arbor Michigan with four band Landsat Thematic Mapper (TM) imagery. The result was change in five different categories, corresponding to changes in relative reflectance, which could be used for latter decision in change of interest. They found that CVA has its most advantages when full-dimensional radiometer change is sought, when all change must be detected and might be of interest. This was shown in a one band CVA compared to a 6-band CVA of Landsat TM in Mizerah, United Arab Emirates. The latter analysis revealed higher information content. A new method combining post classification comparison and a CVA in posteriori probability space (CVAPS) was presented by Chen et al. (2011). The method was applied to Landsat TM and proved to reduce the problem error add up of post classification and to improve detection.

Traditional CVA makes use of the original relative spectral differences in the images at the time of acquisitions. Other input data has been tried out as to target specific kind of change e.g. using tasselled cap). If a specific type of change is wanted and is possible to determine beforehand it’s possible to create spectral features for that purpose to augment the change wanted, for example with statistical procedures. A benefit is the sensitivity to the wanted
change and insensitivity to unwanted changes Johnson R.D & Kasischke E.S. (1998). To solely depend on spectral information can be deceitful since some land cover classes can be similar. Change may have occurred even if spectral change is small and change can also be intra class change generating false change He et al. (2011). Thresholding of traditional CVA can be based on trial and error, empirical strategies or semi-automatic methods that use of the histogram of spectral change-magnitude He et al (2001). Chen J et al (2011) mention that a single threshold for CVA is not appropriate because different change types usually have different dynamic range of change magnitude.

2.2.1.1 Texture and index based classification and change detection

Several authors are evaluating the benefits of introducing textural information and indices in addition to the spectral information in remote sensing analysis. In the literature a range of vegetation indices (VI) can be found, with NDVI regularly used. Siwe and Koch (2008) saw potential in using Tasselled Cap greenness differences for CVA analysis for land cover change (forest) in mount Cameroon region. The technique was implemented on Landsat TM and ETM imagery. Berberoglu & Akin (2009) reported CVA as the best change detection technique using Landsat TM images over image ratioing, differencing and regression using NDVI differences in Mediterranean land use/cover change. Although relatively time consuming, advantages over the other techniques include the possibility to include any number of bands and higher accuracy. Although commonly used Wu, De Pauw and Zucca (2008) mention a concern regarding NDVI since it is affected by the canopy background.

There are also attempts on finding an adequate corresponding Build Up Area Index). Pesaresi, Gerhardinger and Kayitakire (2008) proposed a Built Up Area Presence Index by anisotropic rotation-invariant textural measure using Spot panchromatic data. The Index was based on GLCM texture contrast calculated from a number of directions and the assumption that contrast can be used as built up areas provide high local contrast due to shadow and that buildings are typically in clusters. Ehrlich & Bielski (2011) used this “Built Up Area Presence Index” for change detection using PCA on Spot Panchromatic data of Casablanca with adequate results when the changed areas were large.

Detection of housing development was performed by Zhang, Y. (2001) using a fusion of high spectral Landsat TM data and high resolution SPOT panchromatic data in Shanghai. The
extraction of urban areas included using co-occurrence matrix based filtering (energy, contrast, entropy and homogeneity measure) using the fused data. The use of filtering increased the average Kappa of the class by 30%. Green areas and water was obtained from TM because of the covers homogenous nature. Wang, C. & Zhao Z. (2009) used SPOT 5 data for land cover change detection outside Beijing. NDVI difference was first calculated and unsupervised texture segmentation was performed which included Gabor filtering, contrast, energy, entropy and homogeneity texture measures, independent components analysis and K-means++ clustering with a detection percentage of 0.8071. Yang X. & Liu Z (2005) had Landsat TM and ETM+ data for urban growth analysis and made use of Tasselled cap Greenness and Brightness (discarding Thermal band and NDVI by tests) and created an Imperviousness index using multiple regression analysis. The creation of the index required additional higher resolution data set.

Villa (2007) presented two new indices for detection of impervious/ non impervious surfaces, Soil and Vegetation Index (SVI) and Brilliance Adjusted Soil and Vegetation Index (BASVI) including SWIR data. The indices were compared to known indices such as NDVI, SAVI and UI. Both new indices performed well on Landsat TM and ETM+ data when compared through separability measures.

An attempt of using texture to predict population density on Ikonos data was carried out by Liu, Clark and Herold (2006) in a comparison study of GLCM, Semi-variance and spatial metrics. Although results were not enough to recommend the method as a reliable forecast, some correlation with the logarithm of population density was found. A combination of GLCM textures based on NDVI ($R^2 0.45$) and spatial metrics ($R^2 0.55$) proved the highest correlation. Result also revealed better results for GLCM textures based on NDVI rather than NIR band.

Zhang Q. et al (2003) tested combinations of eight statistical textures (GLCM), a structural texture edge density (ED) and Number of Different Gray Levels (NDG) for classification on panchromatic SPOT. Generally the overall accuracy increased by adding texture up to an input combination of three or four when the accuracy improvement wears off. Of combination of two textures MEAN was always one of the textures performing best. For combinations of four or more, the choice of textures mattered less, performance was
similar. For GLCM textures the results were dependent of the type of area (old city, external city, non-built up in Beijing). NDG and ED did not significantly add to accuracy (more than a GLCM texture) but can replace a GLCM texture for computational purpose.

Maselli et al (2001) used SPOT 10m panchromatic images for urban change detection in Xiamen, China. They used PCA second component to extract change and fuzzy classifier on multi-scale textural filtered images (mean, variability, frequency mode and entropy of three window sizes). This was followed by a maximization step, finding the maximum grade of the fuzzy memberships, leading to the final classification. They found the textural filtering and the multi-scale maximization process effective to use for land cover information taking advantage of the high spatial information of the panchromatic data.

A method proposed by Li, P et al (2007) used a texture based on Pseudo Cross Multivariate Variogram (PCMV) and used in multitemporal classification by SVM for change detection on Landsat TM data in Italy. The texture increased the Kappa values up to 10% compared to results when only using spectral input.

He et al. (2011) performed change detection of rural-urban fringe areas in China. They compared normal and extended CVA, using five textures based on Gray Level Co-Occurrence Matrix (GLCM) as well as the spectral information, followed by Support Vector Machine (SVM) classification. Data from Landsat TM, CBERS and ALOS/AVNIR sensors were evaluated in three areas. The results showed that for each of the compared data sets the Kappa coefficient and overall accuracy was improved by adding textural information. ALOS/AVNIR values improved from 0,66% to 0,81% and 83% to 90,33% respectively. The authors also found that salt and pepper effect was reduced due to reduced omission and commission errors compared to using only spectral information.

Chen & Wang (2010) using Landsat TM/ETM+ and ASTER data made use of slope, NDVI and GLCM textures in a rule based change detection and the result improved overall accuracy and kappa compared to regular MLC classifier. They used The NIR band for calculation of eight textures to improve post classification change detection. Each texture was tested with 3x3 and 27x27 window size for each class. They found that for built-up area the best texture was standard deviation 23x23, for crop field homogeneity 23x23 and entropy 21x21 and for
orange orchards contrast 3x3. The useful window size and texture therefore varied considerably for different classes.

Smits and Annoni (2000) applied a specification-driven change detector using GLCM texture features on SPOT panchromatic data of Thessaloniki, Greece. They discuss that texture features are likely to be less sensitive to misregistration since it is calculated from an area and not a single pixel. They also state the advantage that combinations of texture measures can create representations of the same thing. Also, some characteristics for textures concerning high resolution panchromatic imagery are given. Energy- higher for agriculture, rural areas, urban parks, Entropy – low for vegetation, high for large signal variation. Homogeneity – low for urban etc.

Dalla Mura et al. (2008) used morphological filters and CVA images with pansharpened very high resolution Quickbird imagery for change detection around Trentino, Italy to evaluate two combination methods with Self Dual Reconstruction Filter and Alternating Sequential Filter with a range of filter sizes applied to spectral change vectors. Effects of filtering of the difference image included noise reduction, simplification and maintaining shape. Experimental results show that the percentage of total errors can be reduced compared to standard pixel-based CVA. The performance of the filters is highly dependent on filter size.

Another topic of interest is making the process of change detection automatic. This is particularly of value in cases when time is precious. Lu et al (2011) introduced a semi-automatic method for landslide mapping with Quickbird data and LiDAR using a multi-scale iterative segmentation. Scale parameter and threshold was derived automatically. The classification and change detection made use of PCA, Spectral Angle Mapper (SAM), Reed-Xiaoli detector (RXD) used for spectral anomalies and GLCM textures on the LiDAR data.

2.2.1.2 Extraction of change

For techniques resulting in change/no change classification thresholding is a critical step Ban & Yousif (2012). A suitable threshold is determined somewhere in the histogram tails which contain the change. Two different methods are regularly used, trial and error and statistical measures such as choosing standard deviation from the mean. Two problems with thresholding can be identified, the first is that differences can be caused by factors such as
atmospheric conditions, illumination etc. The other is the subjectivity of the threshold due to both understanding of the study area and competence of the analyst. Despite this, it is still common because it is intuitive and easy to apply. Lu et al. (2004)

In change images that are approximately normally distributed, a value close to mean will indicate similar spectral values on both occasions and that there is no or small change. The further away from the mean it is expected to find greater change. This was tested by Ridd & Liu (1998) for near normal distribution of differencing, ratioing and tasselled cap with 0.1 to 3.0 standard deviations from the mean. The optimal thresholds ranged between $0.7 - 1.7\sigma$.

A chi square distribution was tested using absolute numbers and only one tail threshold was used since the chi square distribution assumes that a value of zero represents no change. Berberoglu & Akin (2009) first applied a logarithmic transformation on their change images from rationing, differencing and CVA since the distributions were not normally distributed. They found $\pm 1.6\sigma$ from the mean was the most accurate. Ngamabou Siwe & Koch (2008) set a threshold at $2\sigma$ for CVA tasselled cap change. Pesaresi, Gerhardinger and Kayitakire (2008) chose a method to look at transects and their spatial profile choosing a threshold for built up membership. Others have worked around the threshold concept and use change images as input to machine learning to classify change/no change. He et al (2011) used training areas (change/no change) of spatial and texture based change magnitude as input for SVM to classify two classes. Li et al (2007) used the same approach with SVM classification for change detection using multivariate texture.

SVM is gaining popularity and SVM has been used for a range of applications, resolutions and spectral resolutions. SVM is a supervised machine learning method. Its non-parametric statistical method meaning it does not assume a statistical distribution of the data (Niu and Ban, 2013). SVM profit on the “structural risk minimization” of the learning process that minimizes classification errors of unseen data, no probability distribution assumed beforehand Mountrakis, Im and Ogole (2011). As it is a classifier it is possible to use for supervised classification of a change variable to obtain a change image.

Huang, Davies and Townshend (2002) tested the influence of training size sample of 2,4,6,8,10,20% of the image and report that 2% gave better accuracies than some higher percentages using equal sample size (RBF and polynomial kernel). They explain this with
saying that the decision boundaries are not statistical attributes depending on size but use the support vectors. They add that the possibility to find the best support vectors to form a decision boundary is probably higher in a larger training set although a small set might include the best while a larger will not. Three factors affected the training of SVM, the training size, kernel parameters settings and class separability. Mixed classes took longer to train and polynomial kernels were slower than RBF. Their results also indicate that SVM had difficulties with few variables (input bands) and were less accurate using 3 versus 7 variables. The problem is ascribed to the transformation of boundaries between spaces. Pal & Mather (2005) compared land cover classification with SVM to result maintained by Artificial Neural Network and Maximum likelihood. They performed a multi class classification and tried both one against all as well as one against one strategy. One against one was faster and gave higher accuracy than one against all. Their results imply that SVM can achieve higher accuracy than ML and ANN and also that it can outperform them using hyperspectral data (high dimensional data set) as well. They also mention that a drawback of SVM is its dependency of few kernel parameters set by the analyst. Lafarge, Descombe and Zerubia (2005) proposed a new textural kernel for SVM classification which includes textural as well as radiometric information where the influence of the two can be weighted. The kernel was tested for both fire detection and urban area extraction on SPOT5 data with satisfactory results. For the urban application the kernel was weighted to be entirely textural.

As opposed to conventional recommendations Foody & Mathur (2006) suggested the use of a few number of mixed pixels in the training stage of SVM for geographical borders. The rational for this is due to the fact that only a few pixels out of the training set constitute the support vector and that the information to separate the classes, to find the hyperplane, lies within these pixels. The aim is to find the best separation information rather than the best descriptive statistics for each class. A comparison of crop classification using mixed pixels and pure pixels showed no significant difference in accuracy.

2.2.2 Object-based change detection

Object based image analysis make use of image objects, segments, rather than pixels. The segments are the basic elements and can generate useful statistical and textural information as well as shape features (size, length etc.) and information of other segments proximity
Benz et al. (2004). Segment outline ought to be as close to the real objects it is representing for the sake of analysis. A common problem is over and under segmentation which can be avoided with multi-scale optimization Lu et al (2011). The object based image analysis is getting increasingly popular and commonly performed using Very High Resolution Imagery (VHR). Change detection using VHR introduces new challenges as same physical objects can have different spectral signatures depending on illumination/shadows, sensor viewing geometry and moisture. This phenomenon makes it harder to obtain consistent segmentation and reliable classification.

Classification using object based approach has already been studied by several authors. Object based classification has been reported by Myint et al (2011) to perform better than traditional per pixel method in high resolution imagery. One cause is that there can be real life object that share spectral characteristic but do not belong to the same class. A discussion on choice of segmentation parameters and scale levels is also comprised in the paper. Jacquin, Misakova and Gay (2008) used a three scale level segmentation for detecting urban sprawl in SPOT 5 imagery using nearest neighbour and fuzzy membership classifier. A hierarchical (local and regional) classification incorporating spatial metrics of segments’ shape (length/width ratio and area) was created. Taubenböck et al (2010) developed a multi-level hierarchical classification framework tested on IKONOS data of Istanbul, Turkey. Classification was carried out by decision fusion based on fuzzy logic including NDVI and length/width ratio. The methods transferability was verified with a Quickbird data set of Hyderabad, India.

A thorough review of the recent progress in object based change detection was given by Chen et al. (2012). They address problems associated with change detection in general, such as viewing geometry and misregistration, as well as difficulties of the object based approach that is scale, comparison of objects and sliver polygons. Four types of object based change detection (OBCD) implementations are identified: image-object change detection, class-object change detection, multitemporal-object change detection and hybrid change detection together with respective realizations.

Doxani, Siachalou and Tsakiri-Strati (2008) used an object oriented method using Quickbird and Ikonos imagery to detect change in Thessaloniki, Greece. Segments were classified with
fuzzy classifier in a multi level approach incorporating NDVI, PCA and the Shadow General Indicator. Change detection was carried out by using sub level segmentation based on the first date classification enabling change/no change sub classes for each class, hence providing to-from information. Lu, D et al. (2010) compared two standard change detection techniques, image differencing and PCA, with a technique involving impervious surface image using matched filtering. Spectral signatures from Quickbird imagery was extracted and clustered with an unsupervised classification and edge based segmentation was performed followed by mean spectral signatures for the segments were calculated. Results concluded that the impervious surface based method outperformed the others. For a shrubland change application Stow et al (2008) used Airborne Data Acquisition and Registration visible and NIR data as well as NDVI and respective segment mean and standard deviation measures to detect increase/decrease. A fuzzy membership function classifier was compared to standard nearest neighbor classifier and the latter showing best results.

Im, Jensen and Tullis (2008) showed that object based change classification using Object Correlation Images (OCI) and Neighbourhood Correlation Images (NCI) performed better in accurately identifying change on a Las Vegas Quickbird data set than object based methods without contextual features or pixel based method, even when including NCI. The information images used was correlation, slope and intercept for objects and neighbourhood respectively. Performance of machine-learning decision tree and nearest neighbour classifiers was also studied. OCI and NCI generated better accuracies irrespectively of classifier. Huang, Zhang and Yang (2010) proposed a method including intensity and texture differences for segmentation on an experimental study on Beijing CBERS-2 data.

Yang et al (2012) proposed a spatio-temporal classification method including contextual information for change detection of urban fringe areas using Landsat imagery of six dates. Object oriented segmentation was used to retrieve the contextual information and a trajectory calibration model for the temporal context information. Spectral classification was combined with temporal and spatial information to form probability of a pixel belonging to a certain class. The integrated method proved to outperform pixel based method.
3. Study area and Data

Stockholm is the capital of Sweden. Stockholm urban area (tätorten), which is the coherent urban area stretching over several municipalities (kommuner), has grown from almost 1 million people in 1980 to almost 1.4 million people in 2010 (scb.se). The prediction for Stockholm urban area is that it will reach 1.695 million by the year 2025 (United Nation). Stockholm has a normal temperature of -2.8°C in January and 17.2°C in July and a yearly normal precipitation of 539.3 mm for the period 1961-1990 (smhi.se). Stockholm County (län) has two national parks and 274 nature reserves, as well as a cultural reserve. It amounts to 7.6% protected nature of the county’s total area (Länsstyrelsen, 2013).

Stockholm is a growing region. Since the late 1970 the newly build apartments in the municipality have been around 2000-3000 and after 2000 approaching 4000 apartments a year (statistikomstockholm.se). At present there are around 30 larger ongoing or planned urban development projects in Stockholm municipality including new city districts and public transportation projects. The city is densified as new districts areas are built on old industrial land (bygg.stockholm.se).

The study area reaches from Upplands Väsby in the North West, Åkersberga north east, Tumba south west and Handen south east and the City of Stockholm in the centre. Stockholm is made up of several islands and a dominating feature is the surrounding water. The major land cover types are water, built up and vegetation. The central parts of the city are made up of high density urban areas with smaller green areas. There are multiple housing complexes and villa areas as well as industrial and commercial areas. In the outskirts of the study area the vegetation gets more dominating, the green wedges pointing towards the centre.

The SPOT system is part of an earth observation program aimed to increase the understanding of the earth. Some applications of the data products are cartography, management of natural resources and planning. (cnes.fr, 2013a) The first SPOT satellite SPOT 1 was put in orbit in 1986 offering multispectral and panchromatic images and possibility of relief mapping with 10m accuracy. SPOT 2 followed in 1990 and SPOT 3 in 1993. SPOT 4 launched in 1998 had increased life time expectancy from three to five years and also included a vegetation instrument intended for worldwide everyday coverage and climate
research. To secure continuity and providing higher spatial resolution SPOT 5 was launched in 2002. (cnes.fr, 2013b)

The first generation of SPOT satellites 1-3 carried HVR (High Resolution Visible) whereas SPOT 4 with HVRIR (High Resolution Visible and Infrared) included an different ranged panchromatic band (0, 61-0,68) and a SWIR band (1,58-1,75) as well as an 1 by 1 km vegetation instrument. These four satellites had spatial resolution of 20m for multispectral band and 10m for panchromatic Jensen (2005, pp. 74-81). SPOT 5 HRG (High Resolution Geometric) had improved spatial resolution of 10m for multispectral and possibility of 2.5-5m panchromatic and HRS (High Resolution Stereoscopic) instrument taking stereo pairs for 3D surface modeling as well as Vegetation 2 instrument (cnes.fr, 2013c)

The SPOT satellites are in sun-synchronous orbit with inclination of 98, 7⁰ at 822 km altitude. The satellites carry two identical high resolution sensors, pushbroom linear arrays having the advantage of longer time to register energy as opposed to swiping whiskbroom sensors. The swath width is 60 km for each sensor with 3 km overlap at nadir making the total width 117km. The revisit time for the satellites is 26 days but the sensors also have off nadir steering capability which enables faster revisit time. For SPOT 1-4 the possible oblique viewing angle is +/- 50,5⁰ and for SPOT 5 +/- 27 Jensen (2005, pp. 74-81)
SPOT 1 XS image from 1986 has three available bands, Green (0,50-0,59 μm spectral range), Red (0,61-0,68 μm) and NIR (0,78-0,89 μm) of 20m resolution. An additional panchromatic data set with higher resolution of 10 m (0,51-0,73 μm) was also used. (astrium-geo.com, 2013) The Panchromatic and multispectral data are actually on year apart but relatively close in time of year. The SPOT 5 data from 2006 has three bands NIR, Red and Green of 10 m resolution and same spectral range as the 1986 dataset. The 2006 image was already georeferenced, mosaiced and cloud corrected. An overview of the study area can be seen in figure 1 showing the fused 1986 data and 2006 data and details about the data in table 1.

The multispectral from 2006 and 1986 are both acquired during the summer period but not at anniversary dates. Therefore some discrepancies in vegetation reflection can be seen between the two years.

Table 1 SPOT Data set

<table>
<thead>
<tr>
<th>Year</th>
<th>Spectral/Spatial Resolution</th>
<th>Radiometric Resolution</th>
<th>Referenced</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006 Aug 5 (part 2008 June 4 , cloud)</td>
<td>SPOT Multispectral</td>
<td>10 m</td>
<td>8 bit</td>
</tr>
<tr>
<td>1986 June 13</td>
<td>SPOT XS Multispectral</td>
<td>20 m</td>
<td>8 bit</td>
</tr>
<tr>
<td>1987 May 22</td>
<td>SPOT Panchromatic</td>
<td>10 m</td>
<td>8 bit</td>
</tr>
</tbody>
</table>
4. Methodology

It is necessary to perform preprocessing before being able to analyze the data. The panchromatic image was first referenced using the 2006 image. Image normalization was then performed between 2006 and 1986 data set to minimize radiometric discrepancies. The multispectral image from 1986 and panchromatic image from 1987 was then fused using wavelet transform to gain same spatial resolution of 10 m as the 2006 image.

The general change detection is based on the methodology of He et al. (2011) who used extended CVA on Landsat Thematic Mapper (TM), China-Brazil Earth Resources Satellite (CBERS) and Advanced Land Observing Satellite (ALOS) data in China. The ALOS/AVNIR with visible and near infrared bands of 10m spatial resolution is comparable to the SPOT data used in this thesis. The extension involves adding several GLCM texture measures to the spectral information when computing the change magnitude which is followed by classifying change using supervised classification. Previous work of Zhang, Q. et al (2003) suggest that not more than three or four texture measures are needed as more does not improve classification results significantly.

GLCM texture measures of different sizes were calculated for both 2006 and 1986 image as well as CVA change magnitude. The change magnitude was calculated from both the spectral information and three chosen texture measures rendering pairs of new input bands for supervised classification using SVM. SVM was then performed using only spectral change magnitude input and for spectral and textural change magnitude input while testing GLCM textures sizes as well as different SVM kernels and parameters for the classification. The results were binary classification image with change and no change. A flow chart presenting an overview of the methodology process can be seen in figure 2.

The two change detection results were compared to see the benefits of adding texture to the spectral data. Accuracy assessment by calculating confusion matrixes were also performed to evaluate the results and the omitted end excluded pixels of the change classification.
4.1 Preprocessing

4.1.1 Geometric Correction

The data sets were not in the same projection. Since the 2006 10 m data already was registered to RT 90 and had the highest resolution the 1987 PAN was registered to that via image to image registration. Any errors present in the original registration will propagate to the new image (Jensen 2005). To relate the images to each other common reference points called ground control points are used. A ground control point is a recognizable object in an image where the coordinates are known. The relationship of the position in the unregistered image is then determined by a chosen math model. It is recommended to choose points close to the ground and from different elevations and to avoid shadowed areas. A 50 m DEM was also included in the registration to achieve as good results as possible.
The collection of GCP is repeated until the RMS of the individual pixels \((x,y)\) or a minimum Total Pixel RMS is accomplished. Features that can be mistaken and have significantly different elevation from each other can make the result poorer quickly and should not be included in the calculations. 15 GCP points were collected with a distribution throughout the whole image. This is for the math model computations to be calculated over the whole image. Undesired distortions can occur in areas that are not covered by the GCP’s due to the mathematical fitting. Jensen (2005, p. 237) mention that higher order polynomials can introduce distortion further away from the GCP’s than linear methods. The aim is preferably to have a minimum of distortion due to resampling during registration. Nearest neighbour resampling method was used.

### 4.1.2 Radiometric Normalization

Because of different conditions during acquisition of the different date imagery the radiometric intensity values are not comparable since they don’t represent the true reflectance of the surface object Yang & Lo (2000). Solar elevation and atmospheric conditions are some factors that have influence during the requisition of the image. Also seasonal differences in vegetation affect the reflectance. It generates the need to normalize the data set.

To be able to make an absolute radiometric correction on site measurements at the time of the acquisition of the imagery is required. Since change detection is an analysis that utilizes data from earlier periods, this is impossible to achieve afterwards. Hence, due to practical reasons absolute radiometric correction cannot be performed. Relative radiometric correction can be performed after the images are acquired. It makes use of the relationship between the radiometric values (DN values) of the two images. The goal is for the values to be comparable, i.e. same object types have same radiometric value in both images, and not for the values to be absolutely true.

Among the relative methods Yang & Lo (2000) compared pseudoinvariant features (PIF), radiometric control set (RCS), image regression (IR), no change set determined from scattergrams (NC) and histogram matching (HM). Relative regression methods are grouped in three subcategories: Statistical Adjustments approach, Histogram Matching and Linear Regression. The methods above all fall under linear regression except histogram matching.
Image regression obtained the lowest average RMSE of the methods of 7,825 and the other ranging from 9,133 to 14,657 and 6,659 compared to 6,953-12,976 for two Landsat data set bands 1-4 of different times. Attention should be addressed to the fact that the best methods in terms of statistics and visual interpretation, IR and NC both indicated a trend of reducing the dynamic range and obtain low values of coefficient of variation which are measurements of dispersion of a distribution. This raises a concern when dealing with classification and spectral separability. Another aspect when using the above mentioned methods is the reduction of magnitude of spectral change which also occurred. It appears that there is a trade-off to consider when choosing method Yang & Lo (2000).

Image regression was performed according to the equations in Yang & Lo (2000):

Transformation coefficients slope \( m \) and intercept \( b \) of band \( k \) are calculated:

\[
m_k = \frac{v_{RES}}{v_{SLR}}
\]

\[
b_k = R_k - m_k \cdot S_k
\]

Where \( R_k \) and \( S_k \) are the means of master and subject image respectively, \( v_{SLR} \) subject variance and \( v_{RES} \) is covariance.

The linear equation below is then used for performing the normalization of the subject image:

\[
S'_k = m_k \cdot S_k + b_k
\]

The coefficients can be based on control sets or pseudo invariant features. Method chosen was to include values of the entire images, using all pixels instead of stratified samples.

Least Squares Regression was also tested and results were compared to the results of linear image regression. Equations from Fan (1997).

Two types of assessments were done to evaluate the result of the normalization. Firstly, a visual comparison is done to see if the normalized image has a visual similarity to the master image. Secondly, the Root mean square error was computed. It is a statistical agreement measure between the images.
\[
RMSE_k = \sqrt{\frac{1}{\text{scene}} \sum_{\text{scene}} (S_k - R_k)^2}
\]

### 4.2 Data Fusion

Fusion of data can use several types of data such as thermal, radar and optical. A common use for image fusion is to combine low resolution image (multispectral) with high resolution panchromatic to obtain a high resolution image with rich spectral content. Especially when using dates from different time periods as in change detection different age of the sensors have different spatial resolution and is not comparable for analysis until data is fused or at least resampled to the same size in the case of change detection.

#### 4.2.1 Data Fusion Using Wavelet Transform

Wavelet transforms like the Fourier transform give information about frequency but additionally the functions they are based on also has a location in space. Amolins et al (2007) The wavelet approach is suitable for fusion because of its ability to overcome the different spatial resolution problem using a multiscale (or multiresolution) approach. Decomposition is performed through a DTW creating coefficients containing image information. These coefficients can be combined from the original images to create new merged coefficients. The image with the fused data is then reversely transformed with an Inverse DWT. An important step is the merging of the coefficients to get the best possible fused image. Several strategies for coefficient combination exists Pajares & Manuel de la Cruz (2004).

An image can be thought of as piecewise-constant functions on the interval \([0,1)\). A vector space in which all functions are contained (and defined for the interval) is called \(V^l\), with constant pieces over \(2^l\) subintervals. To define a basis for the spaces in \(V^l\) scaling functions \(\phi(x)\) are chosen as basis functions for \(V^l\). Also an inner product is chosen for the vector spaces. An orthogonal complement of \(V^l\) in \(V^{l+1}\) can now be defined, called \(W^l\). The linearly independent functions \(\psi^l(x)\) that span \(W^l\) are called wavelets. This is a simplified description, for more detail and mathematical expressions see Pajares & Manuel de la Cruz (2004).
Wavelets can be defined by their scaling and wavelet functions and they have different properties for example compact support and number of vanishing moments which will influence the result. Some conditions on the wavelet function are must be met to ensure invertible Amolins et al (2007). To use a wavelet function \( \psi(x) \) (the mother wavelet) it has to be scaled and translated and often normalized to inherit all wavelet function properties. A so called daughter wavelet can be defined: Amolins et al (2007)

\[
\psi_{a,b}(x) = \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right)
\]

Where \( a \) and \( b \) are real numbers and \( a \) not zero, these are the scaling and translation factors. A common choice is the dyadic sampling setting \( a = 2^{-j} \) and \( b = 2^{-j} k \) with \( j,k \) being integers.

The Haar wavelet was the first function and the most simple. It has support width 1, filters length 2 and 1 vanishing moments for \( \psi \) (MATLAB Help). The function is discontinuous and is a step function when analyzing a continuous variable.

The Haar wavelet is defined by: Amolins et al (2007)

\[
\psi(x) = \begin{cases} 
1 & \text{if } 0 \leq x < 1/2 \\
-1 & \text{if } 1/2 \leq x < 1 \\
0 & \text{otherwise}
\end{cases} \quad \phi(x) = \begin{cases} 
1,0 \leq x < 1 \\
0, otherwise
\end{cases}
\]

The Daubechies family (dbN) is a number of compactly supported wavelets. The number \( N \) is the order of the Daubechies wavelet and it has \( N \) number of vanishing moments for \( \psi \). db1 is equivalent to the Haar wavelet. Coiflet family (coifN) is also orthogonal and has \( 2N \) number of vanishing moments for wavelet function \( \psi \) and \( 2N-1 \) number of vanishing moments for scaling function \( \phi \). Both Daubechies and Coiflets have support width of \( 2N-1 \).

The Biorthogonal family (biorN.N) are compactly supported wavelets uses two wavelets, one for decomposition and another for reconstruction with \( 2N +1 \) support width MATLAB Help (2013).

The wavelet function \( \psi(x) \) represent the high-frequency of a signal whereas the low-frequency part is represented by the scaling function \( \phi(x) \). This can also be seen as the detail and smooth parts respectively of the signal Pajares & Manuel de la Cruz (2004). The wavelet
and scaling function are rarely derived explicitly. The scaling function will be the same as a scaling filter if the wavelet function has compact support which is enough to get the filter coefficients Amolins et al (2007).

For 2-D images the scaling and wavelet functions can be extended giving one scaling function and three wavelet functions. Pajares & Manuel de la Cruz (2004):

\[
\phi_{LL}(x, y) = \phi(x)\phi(y) \\
\psi_{LH}(x, y) = \phi(x)\psi(y) \\
\psi_{HL}(x, y) = \psi(x)\phi(y) \\
\psi_{HH}(x, y) = \psi(x)\psi(y)
\]

For each row the image is passed with a low-pass and high-pass filter and downsampled horizontally which creates coefficient matrixes \(H(x,y)\) and \(L(x,y)\). The filtering and downsampling is then proceeded in the vertical direction for each column in \(H(x,y)\) and \(L(x,y)\) which renders four images \(LL(x,y), LH(x,y), HL(x,y)\) and \(HH(x,y)\). This constitutes one decomposition level. \(LL(x,y)\) can be called the approximation of the original image while the other subimages represent the details in horizontal, vertical and diagonal direction. If several levels of decomposition is wanted, the procedure is iterated using the approximation image \(LL(x,y)\) hence receiving another set of detail images. When the coefficients are fused Inverse DWT is used, creating the final fused image with combined information content Pajares & Manuel de la Cruz (2004). Merging coefficients is only allowed on the same level of decomposition. To do this one must choose a fusion rule and there are several possibilities including: Activity – level measurements, Coefficient Grouping and Coefficient combining (selection, averaging) When using weighted averaging and weight is zero it becomes a pure replacement of the image Pajares & Manuel de la Cruz (2004). This is used for the in panchromatic and multispectral fusion.

The fusion was performed using a multi-level 2-D wavelet technique implemented in Matlab. Four wavelet families, Haar, Daubechies, Coiflet and Biorthogonal were tested using decomposition and reconstruction filters. For each of the families three decomposition levels were initially tested, and the only best candidates continued in level two comparisons. The coefficients of the multispectral image were replaced with the detail coefficient from
the panchromatic image before reconstruction using the zero weight averaging (or replacement) scheme. The results were compared with the three measures below. The measure values are averaged over the whole image. It was also visually evaluated.

4.2.2 Fusion Evaluation
To conclude which wavelet produced the best fusion image qualitative visual examination and quantitative measures can be calculated for the resulting images to evaluate the results in terms of improved detail, colour distortion and similarity of the MS original data.

Three indicators were chosen for the quantitative evaluation. The original multispectral and the fused images are used to calculate the difference in mean which should be close to zero, the correlation coefficient that should be 1 and standard deviation of the difference image which should be low Pajares & Manuel de la Cruz (2004).

4.3 Change detection
Chen et al (2012) stress the importance of considering some important factors when performing change detection namely spatial scale, temporal scale, viewing geometry, image registration, radiometric correction and normalization and features applied in change detection.

4.3.1 GLCM Texture measures
Urban detection is problematic because the objects are complicated and their structure is more characteristic than the spectral reflection. In pixel by pixel methods this is a problem where the spatial component is discarded Zhang, Y. (1999).

Haralick, Shanmugan and Dinstein (1973) described a set of texture measure because spectral, textural and contextual features are important to the interpretation of colour photographs when discriminating features. It is useful to use texture to identify characteristics of image objects or regions of interest. The textural features describe one band spatial distribution of tonal variation whereas spectral features describe average distribution of all bands. The GLCM texture measures are based on dependencies of the gray tones. The calculation is a statistic procedure based on the assumption that that the textures contain average spatial dependency between gray tones in an image.
For a given resolution cell the gray tone spatial dependence matrices are computed. In the original form four such matrices were computed at 0, 45, 90 and 135 degrees relationships between the resolution cell and its nearest neighbours (distance = 1). The relationship of a resolution cell and 0 or 90 degree nearest neighbour is the horizontal and vertical relationship respectively (and 45 and 135 diagonal). The matrix will contain the number of occurrences of a given relationship. From theses spatial dependencies matrixes the textural features are obtained. The matrices are dependent on angle and distance between the resolution cell pairs. Textures will not change under rotation but the matrices will. For this reason is recommended to use two functions for features of any angel and use the average and range, hence making it rotation invariant, when using angular dependent features as input for classification Haralick, Shanmugan and Dinstein (1973). Normally one or a few of the eight directions around one pixel is used Zhang, Y. (1999).

Gray Level Co-occurrence Matrix proposed by Haralick Shanmugan and Dinstein (1973) is the base for a number of common texture measures. Homogeneity, contrast, dissimilarity, mean, standard deviation, entropy, angular second moment and correlation. To use all texture features is not necessary since the texture bands provide redundant information. When the texture bands are calculated they can be used for computing textural change magnitude as opposed to using the spectral change magnitude He et al. (2011).

Hall-Beyer (2007) grouped the measures as:

Contrast group: Contrast, Dissimilarity and Homogeneity

Orderliness group: Angular second moment, Entropy

Descriptive statistics: Mean, Standard Deviation, Correlation

Measures like homogeneity, dissimilarity, entropy and angular second moment are used to improve classification due to suitability to urban areas. Also, the choice of window size is important. Smaller windows may not capture the amount of spatial information required to distinguish all land cover whereas too large window might introduce errors due to overlapping land cover information. A way of testing optimal size is to compute coefficient of variation of the texture measures and classes, depending on window size Puissant, Hirsh and Weber (2005).
Eight rotation invariant textures were calculated: Homogeneity, Contrast, Dissimilarity, Mean Standard deviation, Entropy, Angular second moment and Correlation. The texture calculations were based on all tree MS SPOT bands and three sizes of filter were tried: 7, 9 and 11. The distance parameter was one. The textures were compared visually and of the eight textures there were a few that seemed to separate well between urban and vegetated area, Mean, Entropy, Homogeneity and Angular second moment. The three first were selected to be used in the analysis.

The three chosen texture measures are from different categories above (contrast, orderliness, descriptive) which also ensures that the information is not redundant.

Equations from Geomatica Tex tutorial:

\[
\text{Entropy: } \sum_{i,j=0}^{N-1} -P_{i,j} \log e(P_{i,j})
\]

\[
\text{Homogeneity: } \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i-j)^2}
\]

\[
\text{Mean: } \sum_{i,j=0}^{N-1} i \cdot P_{i,j}
\]

Where N is the number of gray levels and P is the Normalized symmetric co-occurrence matrix.

**4.3.2 Change Vector Analysis**

Change vector Analysis first presented by Malila, W (1980) is the concept of the computation of a spectral change vector from two spectral images of different dates and the comparison of the change magnitude to a set threshold. The second part of the concept is the direction of the change vector that can contain information of the type of change that has occurred.

Advantages with the CVA method are that all available bands can be included in the analysis and it is possible derive to-from information. Disadvantages include condition of reliable radiometry (effecting factors such as atmospheric condition, soil moisture, solar angle, vegetation and phenology), the lack of automated thresholding and discrimination of types of change Chen et al (2003).
CVA builds upon the change vector which can be defined by two measures: a change magnitude between two dates and a change direction or change angle between dates \( t_1 \) and \( t_2 \). \( H = (h_1, h_2, ..., h_n)^T \) and \( G = (g_1, g_2, ..., g_n)^T \) are the pixel grey levels at \( t_1 \) and \( t_2 \) and \( n \) number of bands. \( \Delta G \) hold the per pixel change information Chen et al (2003).

The change vector is then defined by:

\[
\Delta G = H - G = \begin{pmatrix}
  h_1 - g_1 \\
  h_2 - g_2 \\
  \vdots \\
  h_n - g_n
\end{pmatrix}
\]

The change magnitude, characterizing the total gray level difference, is calculated by:

\[
\|\Delta G\| = \sqrt{(h_1 - g_1)^2 + (h_2 - g_2)^2 + ... + (h_n - g_n)^2}
\]

The larger \( \|\Delta G\| \) the large possibility of change.

CVA is useful when spectral change of change of interest is not known a priori, when high spectral variability in change is expected, and when the change in both land type and its condition is sought. A limiting aspect of CVA is that the change vector holds dynamic change and not the actual state of the pixel which is problematic in the process of categorizing change Johnson R.D & Kasischke E.S. (1998). The state information can be derived from ground truth, interpretation or classification. Using only state information might prove problematic due to omission and commission errors of classifications and can mistake intra class for change between classes, a problem that can be amended by combining radiometric change with state information. The change vector directions are the most useful when “phenomenologically-relevant spectral features” are used as input rather than original data. That is, increase and decrease in vegetation Tasselled Cap features indication vegetation loss Johnson R.D & Kasischke E.S. (1998).

Chen et al (2003) name three methods of categorizing type of changed pixels namely trigonometric functions, sector coding and PCA for discrimination of change type. The task of identifying the types of changes and interpreting is problematic. Sector coding produces \( 2n \) sectors for \( n \) bands and a code might represent more than one type of change.
In most CVA application only two bands are used and thus the direction can be trigonometrically computed. Warner, T. (2005) discussed a multidimensional extension, hyperspherical direction cosine and the direction of change vector with more than two band input using a projection onto a hypersphere. Other has avoided the dimensionality problem by using the magnitude information only.

CVA change vector and change magnitude was computed for the MS SPOT bands and for the selected three GLCM textures of different filter size.

4.3.3 Supervised Change Detection Using Support Vector Machine

SVM searches for the optimal separating hyperplane to separate two classes of training data in n-dimensional space with two parallel hyperplanes. The optimal hyperplane separates the data with maximum margin, an optimization problem of minimizing the norm of w. The parallel planes are constituted of the points called support vectors. The optimization will, under constraints, finally form a decision rule that will separate the two classes. The data may not be separable and therefore two additional variables are used namely a penalty parameter C and slack variable psi. The penalty parameter is a value relating to misclassification errors and psi is related to the optimal separating hyperplane and the training points on the wrong side of the optimal hyperplane Huang, Davies and Townshend (2002).

For a nonlinear decision function the following is concept is used. The input vector is mapped into a high dimensional feature space where the optimal separating hyperplane is constructed. A kernel function is introduced which makes it possible to train and classify without explicitly knowing the mapping function in high dimensional space Huang, Davies and Townshend (2002).

One of the difficult choices the analyst has to make is to choose a kernel. There are several kernels such as the radial basis function and the polynomial kernels and it has been indicated that they produce different results for remote sensing applications. Another consideration that has to be addressed is the c parameter that maximizes the margin and minimizes error for which there is available heuristic yet Mountrakis, Im and Ogole (2011).

The tested kernels are defined as: equations from ENVI:
Linear: \[K(x_i, x_j) = x_i^T x_j\]

The radial basis kernel: \[K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0\]

Polynomial: \[K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0\]

Sigmoid: \[K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)\]

Where \(d\) is the polynomial degree and \(r\) is a bias term set by the analyst.

The two change magnitude files containing multispectral and textural data were the input of the SVM. The original data set as well as Google Maps was used to find training and verification areas for change/no change classes throughout the scene by manual interpretation. SVM was run on only the multispectral change magnitude (one band input) and with both multispectral and textural change magnitude (two band input) to determine the possible advantages or disadvantages the extra input of textures could provide. For this first purpose the Radial Basis Function kernel, gamma 0.5 and penalty parameter 100 was used.

First, confusion matrices of the change/no change results were calculated to determine the best size of GLCM filter. Once established which filter size that proved the highest accuracy, other parameters of choice (kernel, soft margin, and gamma) were tested only for that size. Secondly, four kernels were tested using the same parameter settings as mentioned above, Linear, Radial Basis Function, Second degree polynomial and Sigmoid. Statics were calculated for these kernels performance and compared visually. Penalty parameter (also referred to as C) of different magnitudes were examined. It controls the degree of allowed training errors compared to the margin. A larger value generates a more exact model of the expense of generalization of the classification result.

Training pixels throughout the image were chosen as input to the SVM. 1032 pixels were chosen for each of the two classes. For the results to be true all kind of change was included (including non to non-urban change) to not make the results misleading since the classes do not discriminate different kinds of change. The result of the SVM is directly dependent of the training or the choice of the support vectors.
4.3.4. Accuracy Assessment

Accuracy assessment was performed for the SVM change classification. To evaluate the results and compare them a set of ground truth pixels were chosen for each class, 1003 for change and 2003 for no change class. Using the classification results and the validation data a confusion matrix was computed for change and no change classes. From the confusion matrix some measures was computed including users accuracy (correctly classified pixels dived by all classified of a class) and producers accuracy (correctly classified pixels dived by total number of ground truth pixels of a class). The commission and omission error reflect the amount of wrongly included or excluded pixels respectively. An overall accuracy value and kappa coefficient of agreement was also computed. The overall accuracy is obtained by taking sum of correctly classified pixels divided by all ground truth pixels.

Kappa coefficient is a measure of agreement between the classification and the ground truth data compared to the chance agreement. An estimate of the Kappa Coefficient of agreement is computed by:

\[
K = \frac{N \sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k} (x_{ri} \cdot x_{ri})}{N^2 - \sum_{i=1}^{k} (x_{ri} \cdot x_{ri})}
\]

Where N is the total amount of ground truth pixels, \( x_{ii} \) is the sum of correctly classified pixels, \( x_{ri} \) and \( x_{si} \) are the row and column totals respectively for each class and k is the number of classes. Moderate agreement obtain values between 0,40-0,80 and values greater than 0,80 indicate strong agreement Jensen (2005, pp. 506-508).

In addition the total change area in percent was also calculated to compare the actual amount of change detected for the two classification results.
5. Results and Discussion

5.1 Preprocessing

Total RMS error of georeferencing of the panchromatic image was 0, 38 pixels. The X RMS error was 0, 23 pixels and Y RMS 0, 30 pixels. Since this was done to the 2006 image because of the higher spatial resolution the basic condition was not ideal due to the time difference in acquisition.

Two types of normalisation were tested and Image Regression was the final choice of regression method. RMSE error of IR and LS was in the same range but IR proved to have better min-max values and mean values in accordance to the 2006 scene as seen in table 2. Based on this IR was chosen.

<table>
<thead>
<tr>
<th></th>
<th>G</th>
<th>R</th>
<th>NIR</th>
</tr>
</thead>
<tbody>
<tr>
<td>IR</td>
<td>RMSE</td>
<td>6.982</td>
<td>8.301</td>
</tr>
<tr>
<td>LS</td>
<td>RMSE</td>
<td>7.262</td>
<td>8.096</td>
</tr>
<tr>
<td>1986 original</td>
<td>Min</td>
<td>10</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>254</td>
<td>254</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>35.117</td>
<td>23.723</td>
</tr>
<tr>
<td></td>
<td>Mode</td>
<td>30</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>Sd</td>
<td>7.902</td>
<td>8.908</td>
</tr>
<tr>
<td>1986 IR</td>
<td>Min</td>
<td>39</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>255</td>
<td>255</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>102.955</td>
<td>79.267</td>
</tr>
<tr>
<td></td>
<td>Mode</td>
<td>94</td>
<td>65</td>
</tr>
<tr>
<td></td>
<td>Sd</td>
<td>14.331</td>
<td>19.113</td>
</tr>
<tr>
<td>1986 LS</td>
<td>Min</td>
<td>0</td>
<td>0</td>
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<tr>
<td></td>
<td>Max</td>
<td>237</td>
<td>210</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>102.458</td>
<td>78.220</td>
</tr>
<tr>
<td></td>
<td>Mode</td>
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<td>44</td>
</tr>
<tr>
<td></td>
<td>Sd</td>
<td>26.428</td>
<td>42.996</td>
</tr>
<tr>
<td>2006</td>
<td>Min</td>
<td>69</td>
<td>42</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>254</td>
<td>254</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>102.838</td>
<td>79.359</td>
</tr>
<tr>
<td></td>
<td>Mode</td>
<td>85</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td>Sd</td>
<td>21.478</td>
<td>29.198</td>
</tr>
</tbody>
</table>
5.2 Data Fusion

Four wavelet families Haar, Daubechies, Coiflet and Biorthogonal wavelets of different order were tested on the Stockholm data set, three decomposition levels were tested and the replacement merging schemes for the wavelet coefficients. Mean difference of original image and fused image, correlation coefficient and standard deviation of the difference image was calculated to compare the fusion results. The statics are averaged for all three bands.

Levels of decomposition

The wavelets were at first compared at three levels of decomposition. It is obvious that the fusion images, despite level, have an increased amount of information compared to the original containing only the multispectral data. The statistics in table 3 show that a lower level of decomposition gives better statistical result but in qualitative visual inspection the details in the image are not satisfactory in level one. It is clear that only one decomposition level does not include enough detail for the result to be satisfactory. Two levels seem to give the best trade-off between detail and statistics whereas three levels show declining statistical results (higher standard deviation and lower correlation coefficient) and also artefacts are introduced in the image.

Table 3 Example of fusion results, Mean Difference, Correlation Coefficient and Standard Deviation at fusion level 1, 2 and 3

<table>
<thead>
<tr>
<th></th>
<th>Level 1</th>
<th></th>
<th>Level 2</th>
<th></th>
<th>Level 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>-0.1242</td>
<td>0.976</td>
<td>2.69</td>
<td>-0.0305</td>
<td>0.947</td>
<td>4.04</td>
</tr>
<tr>
<td>Db2</td>
<td>0.0007</td>
<td>0.978</td>
<td>2.51</td>
<td>0.0009</td>
<td>0.956</td>
<td>3.61</td>
</tr>
<tr>
<td>Coif1</td>
<td>0.0006</td>
<td>0.980</td>
<td>2.43</td>
<td>0.0008</td>
<td>0.957</td>
<td>3.58</td>
</tr>
<tr>
<td>Bior1.3</td>
<td>-0.0015</td>
<td>0.975</td>
<td>2.76</td>
<td>0.0007</td>
<td>0.946</td>
<td>4.07</td>
</tr>
</tbody>
</table>

Daubechies, Coiflet and Biorthogonal wavelet families showed that level two yielded the best visual result and that a smoothing effect got more apparent with each increased level. This is particularly bad for the more homogenous vegetated regions. The border between water and land also got blurred, particularly clear in urban/water. Some features like roads
and irregular shaped objects did get sharper and edges got easier to distinguish (higher detail) but the disadvantage of smoothing is predominating.

This effect can be seen in figure 3 highlighting the two effects in an urban area. The distinct road pattern emerges increasingly at each level. Unfortunately the stadium is smoothened in an undesired manner where also the distinct red of the grass court in the middle of the stadium disappears in level three. This is unwanted colour distortion.

![Figure 3](image1)

Fig 3. Detail of city centre, fusion of Db15 level 1-3

![Figure 4](image2)

Fig 4. Water border and city centre, fusion of Db15 level 1-3

The effect is also apparent at the water/road edge of Strandvägen in figure 4. A small high reflectance object in the water is smoothened out and becomes indistinct and hard to interpret as anything else than artefacts in the water in level three whereas the road by the water, streets and piers are more distinct as the level of the fusion increases.
**Fusion results**

Within the Coiflet family fusion of order 1-5 was performed. Visually the results of all the Coiflets are very close and do not display a substantial improvement although the correlation coefficient indicates that a higher order is better. The best result is consequently obtained by the Coiflet with the longest filter length of 30 with correlation coefficient of 0.962. The Daubechies wavelets also have increase of the correlation coefficient as the order increase. The improvement wares of at an order higher than 10 from the tested Db2-15. Statistically Daubechies10 and the best Coiflet member Coiflet5 are equal. Comparison of filter length indicates that Daubechies length 20 and Coiflet length 30 yield the same result. For both families an increase in filter length improves the result. Daubechies15 and Coiflet5 have the same length of 30 but visually Daubechies is slightly better. Bior1.1, Bior1.3 and Bior1.5 create a very apparent block effect that is undesired in the fusion product. This is also apparent in the Haar result.

As for the Daubechies and Coiflet families the filter lengths also matter for Bior family. Biorthogonal families are made up of two filters, decomposition and reconstruction. Bior2.2-8 obtained results ranging between 0.958-0.959. Corresponding number for Bior3.1-9 are 0.949-0.961. Bior4.4 and Bior5.5 got 0.960 and 0.961 respectively. In the Biorthogonal family the best results were obtained by Bior6.8 (length 18, effective length 17/11) at 0.961, a result that is slightly lower than the result of the best Coiflet family member Coiflet5. The visual comparison of those two best statistics confirms a better fusion result.

Comparing the means difference proved not reveal any information about the fusion results as the values were similar around 0.0007-0.0009 for almost all result except for deviating higher values for Haar, Bior1.1 and Bior 1.5. Table 4 gives account for all the tested wavelets at level 2. Comparing all results it is clear that there are no major differences that can be seen in the values of the quality indicators.
Table 4 Wavelets level 2 fusion results, Mean Difference, Correlation Coefficient and Standard Deviation evaluation metrics

<table>
<thead>
<tr>
<th></th>
<th>MD</th>
<th>CC</th>
<th>SD</th>
<th></th>
<th>MD</th>
<th>CC</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>-0.0305</td>
<td>0.947</td>
<td>4.044</td>
<td>Bior1.1</td>
<td>-0.0305</td>
<td>0.947</td>
<td>4.044</td>
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<tr>
<td>Db2</td>
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<td>0.956</td>
<td>3.614</td>
<td>Bior1.3</td>
<td>0.0007</td>
<td>0.946</td>
<td>4.068</td>
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<td>Db3</td>
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<td>0.958</td>
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<td>Bior1.5</td>
<td>0.0012</td>
<td>0.944</td>
<td>4.122</td>
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<td>Db4</td>
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<td>0.96</td>
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<td>Bior2.2</td>
<td>0.0007</td>
<td>0.958</td>
<td>3.494</td>
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<tr>
<td>Db5</td>
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<td>0.96</td>
<td>3.364</td>
<td>Bior2.4</td>
<td>0.0008</td>
<td>0.959</td>
<td>3.434</td>
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<tr>
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<td>0.961</td>
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<td>Bior2.6</td>
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<td>0.959</td>
<td>3.423</td>
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<td>3.328</td>
<td>Bior2.8</td>
<td>0.0007</td>
<td>0.959</td>
<td>3.42</td>
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<tr>
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<td>3.316</td>
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<td>0.0009</td>
<td>0.949</td>
<td>3.867</td>
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<td>0.0007</td>
<td>0.958</td>
<td>3.457</td>
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<tr>
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<td>Bior3.5</td>
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<td>3.378</td>
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<tr>
<td>Db11</td>
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<td>0.0007</td>
<td>0.96</td>
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<tr>
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<td>Bior5.5</td>
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<td>0.96</td>
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<td>Bior6.8</td>
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<td>0.961</td>
<td>3.32</td>
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<td>Coif5</td>
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<td>3.297</td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig 5. Detail of Kungsholmen, best candidates

The best results at level two for each family are Daubechies15, Coiflet5 and Bior6.8 which all are good candidates for the final fusion image. A comparison of the statistical results can be found in table 5. The respective filter lengths are 30, 30 and 17/11 and indicate an agreement in appropriate filter length for the data set. As can be seen in figures 5 and 6 the
visual differences between the best result candidates are slight. The two images represent both high density urban area and infrastructure with vegetation and have very different land use and geometrical features. Despite this it is hard to recognize one fusion result with an advantage over the others as seen in figures 5 a-d and 6 a-d. This is also supported by the statistical measures results.

![Images of images](image)

a) Original MS  b) db15  c) coif5  d) bior6.8

Fig 6. Road 73, best candidates

Table 5 Best result for each family at fusion level 2, Mean Difference, Correlation Coefficient and Standard Deviation evaluation metrics

<table>
<thead>
<tr>
<th></th>
<th>MD</th>
<th>CC</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Db15</td>
<td>0.0008</td>
<td>0.962</td>
<td>3.28</td>
</tr>
<tr>
<td>Coif5</td>
<td>0.0008</td>
<td>0.962</td>
<td>3.30</td>
</tr>
<tr>
<td>Bior6.8</td>
<td>0.0008</td>
<td>0.961</td>
<td>3.32</td>
</tr>
</tbody>
</table>

The results show that for this type of fusion there are several wavelet families that obtain similar results and can be used for purpose of image fusion of panchromatic and multispectral SPOT data of two resolutions. There are only insignificant differences, both visually and statistically.

Only one of the fusion results was used for the analysis and Db15 was chosen due to being a commonly used wavelet and that the statistical result was slightly better when comparing the three measures of the fusion results. Close ups of the final fusion Db15 can be seen in figure 7.
A great deal of improvement of the buildings forming a “circle” is apparent in figure 7a. In reality it is not a full circle but several curved buildings. In the original image it is hard to see the difference between building, shadow and the vegetation in between. Even if the result is not perfect it is easier to make out the buildings which constitute the formation after fusion. The geometry of the buildings are improved after adding the panchromatic detail information. The same improvement is even more emphasized in the second smaller close up in figure 7a. The irregular shape that look like one structure now indicate that it is made out of several separate bodies, which was not possible to see in the original image.

In 7b there is a significantly higher detail in the intricate road system. The streets cover almost all possible directions and in the low resolution image only make the straight linear road in south-north or east-west direction of the pixels discernible. After fusion it is possible to make out the individual houses in the circled part as well and the street pattern is more coherent.

In Vårby the most noticeable enhancement are the piers (circled in 7c). After fusion it is easy to distinguish five separate objects in contrast to the water as opposed to the original image where the piers and the water are constituted by mixed pixels that are difficult to analyze. Unfortunately it is also noticed that a haze is introduce to the fusion result. In figure 7d, first
row, we can make out a high reflectance urban area with elements of vegetation (the original image). Shadowing and resolution make it difficult to distinguish between any geometrical features. Fusion makes a huge improvement in this area making it possible to understand the general character of the area, the blocks and the shape of some buildings.

The added information after the fusion makes it possible for the analyst to perceive more with the eye as well as the increased information enables added input data for further computer aided analysis.

5.3 Change Detection

First eight GLCM texture measures were calculated: Homogeneity, Contrast, Dissimilarity, Mean, Standard Deviation, Entropy, Angular Second Moment and Correlation. Combinations of the textures were viewed in a RGB combination to decide which textures contained most information and which textures were redundant.

The final textural input layer for the SVM based on change magnitude of Homogeneity, Mean and Entropy were tested for three filter sizes 7, 9 and 11 using default parameters settings. The best statistical results were obtained by filter size 9 and consequently the continued SVM input change magnitude layer for the rest of the analysis.

Nonlinear SVM classification to detect change/no change was performed. SVM kernel types Linear, Radial Basis Function (RBF), Second degree polynomial and Sigmoid were tested. Although very small detectable changes in resulting classification performance, statistical comparison revealed the Radial Basis Function to perform most accurately out of the kernels tested.

It was hard to find any common recommendations on how to choose or test the SVM parameters, the kernel parameter setting. There are several software implementations and some papers introduces own kernels and implementation with widely varying parameter values. As a result of this the parameters were tested and evaluated with trial and error.

Penalty parameter of different values was the next parameter to change. At a default value of 100, steps up to 300 was run on The GLCM size 9 and using the RBF. It seems that the SVM is relatively insensitive to the penalty parameter in this analysis. Values of 125-225
yielded the same overall accuracy and kappa. This is related to the choice of training and the support vectors.

Table 6 Comparison of Texture size input and kernel

<table>
<thead>
<tr>
<th>Test parameters</th>
<th>OA</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBF g=0.5/p=100/RBF</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7*7</td>
<td>96.84%</td>
<td>0.9287</td>
</tr>
<tr>
<td>9*9</td>
<td>96.94%</td>
<td>0.9311</td>
</tr>
<tr>
<td>11*11</td>
<td>96.87%</td>
<td>0.93</td>
</tr>
</tbody>
</table>

**Kernel 9*9, default settings**

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear (p=100)</td>
<td>96.37%</td>
<td>0.9187</td>
</tr>
<tr>
<td>Polynomial (deg2/ g=0.5/p=100)</td>
<td>96.91%</td>
<td>0.9306</td>
</tr>
<tr>
<td>Sigmoid (bias=1/g=0.5/p=100)</td>
<td>95.38%</td>
<td>0.8972</td>
</tr>
</tbody>
</table>

Table 6 show the results of the different input setting (different size of texture and kernel). The larger texture size, the more smoothened or generalized texture will be. These sizes all proved to obtain high overall accuracies over 96%, the best of them being size 9*9. Then different kernels were tested for that size. The results show that the kernel getting the best results is the RBF kernel. The others also performed well and got overall accuracies over 95%. A comparison of results between only spectral and adding texture using different parameters is seen in table 7.

Table 7 Comparison of results of SVM with and without texture input

<table>
<thead>
<tr>
<th>Test parameters</th>
<th>OA</th>
<th>Kappa</th>
<th>OA</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No texture</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBF penalty, g=1</td>
<td>87.76%</td>
<td>0.742</td>
<td>87.76%</td>
<td>0.742</td>
</tr>
</tbody>
</table>

With a methodology using CVA change magnitude and SVM supervised change detector with two classes change and no change it is possible to obtain good results by using only multispectral data and derived textures. However, in the field of urban remote sensing, it is sought after to be able to distinguish between several classes such as urban change (new
built up areas) and change in vegetation due to differences of agricultural state, cut trees, etc. More classes are needed to make these distinctions. The methodology followed in this thesis only admits change or no change.

Problems with this classification is for instance that if a building changes the material on the roof it will have a different response and thus will be classified as change although the purpose is not to find interurban change but rather urban growth. Other change that might not be wanted but is present in the result is change due to seasonal changes in agricultural patches, and to some extent, differences in leave response in forest areas, and the grass fields.

A clear advantage of adding texture is that the texture removes noise that is apparent in the multispectral classification results. The texture is an effective way to reduce the single pixels that are classified as change in areas where no change has appeared.

The result of the change detector is dependent on the result of the preprocessing i.e. the co-registration and the fusion result of the 20m and 10m data. Although the data is radiometrically normalized roads are a clear example that the results can benefit from texture where the response is not exactly corresponding (or appears different due to the fusion). A small shift due to co-registration can give rise to undesired false change. This is also reduced using texture.
The analysis using only spectral information show that 7.97% of the total study area has changed. This number is drastically reduced to 4.30% for change classification including texture. In the change images of the whole study in figure 8 it can be seen that less change is found in the central parts of the city and also smaller change areas are reduced when adding texture. Both methods find the majority of change in the outer parts of the study area. This seems realistic since the inner city mostly is high density build up and not likely to change over time.
In Gribbylund, figure 9, first row, both detectors correctly recognize the new road in the top of the image and that there is a major area of urban development and change in an area which previously partly dominated by vegetation. Also there seem to be a densification in the lower part of the close up and a change in character. Comparing the two change result images it is obvious that spectral only detects more change than if adding texture. The existing road to the left is wrongly detected by only spectral.

In Länna, Huddinge seen in figure 9 second row, there is an expanding industrial area in north–west and small residential housing south-east. Both areas seem to have expanded a lot during the 20 years that elapsed between the images. It is apparent that the spectral only discover small areas which the texture smoothens out. The difference is that texture makes
A more “coherent” change whereas spectral also can include a larger number of smaller change areas. This is related to the texture size window.

Täby, seen in figure 9, third row, have very different change results when the using texture or not. For texture only this is an example of how differences in radiometric response (or effects of the fusion) can cause false change due to differences in surface reflection, shadows and maybe seasonal variation of vegetation between the dates. At a first glance is almost looks like the error is due to misregistration although this can be dismissed since the false change is indifferent to direction. The texture alleviates this problem and reduces the found change.

Table 8 Change detection statistics of spectral input only

<table>
<thead>
<tr>
<th>Class</th>
<th>Commission (Percent)</th>
<th>Omission (Percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td>25,06</td>
<td>4,89</td>
</tr>
<tr>
<td>No Change</td>
<td>2,83</td>
<td>15,93</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Class</th>
<th>Prod.Acc. (Percent)</th>
<th>User Acc. (Percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td>95,11</td>
<td>74,94</td>
</tr>
<tr>
<td>No Change</td>
<td>84,07</td>
<td>97,17</td>
</tr>
</tbody>
</table>

Even though neither overall accuracy nor kappa at 87,76% and 0,74 is particularly bad results there are some other apparent problems with the spectral only change detection. Commission error of change class is at 25,06% which is not acceptable. Also 15,93% of no change is omitted. This leads to an overestimation of detected change that is misleading. This is also a confirmation of what could be seen in the change result images. There is also unevenness within the classes, either a very high or very low percentage of the omission commission results. While the commission of change is high, it is low for omission of change. The opposite apply for the no change class. This can be indication of that the input data does not produce a rigid result for the change detection purpose. The producers and users accuracy range between 75-97%. All statistics of spectral change detection can be seen in table 8.
The overall accuracy of the combined textural and spectral input for change detection is exceptionally high at 97.01% as seen in Table 9. This can be attributed to the thorough choice of training pixels and the fact that only two classes are involved. There are fewer classes to be confused and to lower the accuracy of the result than if there were a full land use classification. After adding texture the magnitude of the errors are fairly equal for both change and no change class. The texture seems to add some clarity to the problematic change class, making it more stable. It reduces the problem with extremely overestimation of change although there is still 4.21% omission error left. The results are slightly better for no change class (~2%) than for the change class (~4-5%) for commission/omission errors and ~97% no change and ~95% for producers and users accuracy respectively. Benefits of adding texture seen in these numbers are foremost the reduction of change commission error and omission of no change error. The omission of change and commission of no change were low to begin with and did not reduce notably.

An additional evaluation of the two best change results (with and without texture) was performed due to the high overall accuracy and kappa coefficient. A new set of ground truth pixels were chosen by another analyst in order to validate the results objectively. A new confusion matrix was computed, this time with 791 pixels chosen for no change class and 708 for the change class. For change detection using only multispectral data the overall accuracy was 76, 12% and kappa coefficient 0.53. For change detection result with added texture measures the overall accuracy became 85,80% and 0.72. The validation show clearly reduced numbers for both values. The no change class commission error was reduced from 15,69 to 7,25%. Omission error for the same class reduced from 32,47 to 20,73. Commission error for change dropped from 13,98 to 6,92% and commission error from 29,84 to 19,93% which mean that the errors reduced about 7-11% when adding texture. Both change

Table 9 Change detection statistics of spectral and textural input

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td>4.21</td>
<td>4.79</td>
<td>Change</td>
<td>95.21</td>
<td>95.79</td>
</tr>
<tr>
<td>No Change</td>
<td>2.39</td>
<td>2.1</td>
<td>No Change</td>
<td>97.9</td>
<td>97.61</td>
</tr>
</tbody>
</table>

Overall Accuracy 97.01%
Kappa Coefficient 0.93
classification has a problem with including too much change and leaving out no change which altogether lead to an overestimation of change. The validation conveys two things. The general improvement of added texture and the problems encountered with commission and omission errors when not using textures follow the same pattern as before. There is a near 10% overall accuracy improvement when adding texture and still a change overestimation problem. Secondly, results can vary considerable from an analyst to another and the individual experience, interpretation and knowledge about the area will affect the result.

5.4 Discussion

The choice of change detection methodology includes at least to steps firstly to obtain a change variable and then to extract the change. Depending on combination of these two and also the possible input data for the analysis it quickly gets hard to overview all possibilities and compare them fairy. Furthermore, the individual choices of parameter settings are numerous. This will naturally have impact on the final result.

Registration of the data sets should be accurately executed it will also introduce a possible source of false change. In this thesis a subpixel result was achieved. Differences in radiometric response can also cause false change if normalization is not properly done. The dates of the images are not anniversary which means there is big risk of introducing unwanted change due to the vegetation reflectance depending on the time of year. Even though the images are normalized, differences are sure to be included as change.

The question of what is real or relevant change is difficult. Individual interpretation and a subjective choice in the analysis affect the result as well as how the result should be understood by others. Even though land use classes are not defined for this analysis the question remains if for instance there is change if there is a new roof covering of a different type of grass in a park or even just a change in grass health. This is a subjective choice of the analyst while training the change detector and it will affect the result.

A limitation of CVA change magnitude is that is does not differentiate between type of change if not the change angle is also computed (which also needs interpreting). But depending on input of data or index it might be hard to get a meaningful description or
meaning of the change angle. A strength of CVA is that it is possible to use all information, using all bands, as compared to methods when only two bands are ratioed for example univariate image differencing using 2 bands or indices. CVA made it possible to make use of both the spectral information and the derived textures.

As reported by others the texture greatly improves the results compared to using only spectral information. Fewer textures were used than by He et al (2011) but still with less information (three compared to five) the overall accuracy improvement. The improvement of the result is also in accordance with previous reports by Zhang Q. et al (2003) that more than 3-4 texture measures will not increase classification results much more.

The very high accuracy that was first obtained may have been caused by several factors. Firstly the classification scheme of change/no change classes probably influence the accuracy since there are only two classes for possible confusion as opposed to confusion among numerous land use classes. The choice of training pixels is an issue; they may be picked in very homogenous areas or in the fringe of change area. Availability of older reference data dating as far back as the analysis can be also problematic. Moreover, experience of the analyst is also a factor. It proved to make a large difference when evaluating the accuracy with an independent ground truth set.

SVM supervised classification avoids the issue of thresholding but add a subjective factor in the classification of the change magnitude to change and no change. Also the training of SVM is about finding the best support vector for the decision boundary and it may not actually be found the chosen training pixels.
6. Conclusion and Future Research

Fusion using wavelets proved an adequate method aiming to inject panchromatic detail into low resolution multispectral data with the purpose of higher spatial resolution. Of the different families tested it was shown that Daubechies, Biorthogonal and Coiflet all had potential to be used for further analysis. Some general drawbacks are still noticeable such as a haze effect.

A comparison between different wavelet families showed that there are several possible candidates that attain equally good results and can be used for fusion. Both statistically and visually the fusion images are alike for Daubechies 15, Biorthogonal 6.8 and Coiflet 5. For the data use of 20m and 10m SPOT for fusion two levels of decomposition levels was the most suitable choice of three tested levels. Level two was the best trade-off between visual artefacts and the statistical result.

The SVM performed well as a change detector. The best result was achieved with RBF kernel. It has the limitation of only separating between two classes in the original form but can be extended for more classes. An innate downside is that the method is supervised hence associated with subjectivity. Theoretically it should be possible to have other change variables as input for SVM classifier such as image ratios or difference images.

The change detection results show that change detection using only the spectral data had problems mainly in including too much change but also leaving out no change. This was reduced when adding texture to the analysis. A great improvement can be obtained if adding texture. The three GLCM textures Homogeneity, Mean, Entropy were used and improved the overall accuracy with close to 10% (units) and the kappa value increased from 0.7420 to 0.9326. This thesis shows that it is possible to greatly improve the result with only three texture measures.

A general limitation of the analysis has been the older SPOT data set, its spectral range. Seeing that it is common to use mid infrared bands in urban applications it has had a limiting effect in the search of possible indices, textures of indicators found in the literature.

Further research can be made including:
- Testing exactly which and how many GLCM textures need to be added and still improve the result to satisfactory levels. For this analysis three specific texture measures were chosen but there can be other combination of textures or it might enough to use only one extra texture added to the spectral data to sufficiently improve the results of change detection.

- Broaden the analysis to include more classes and make it an urban change detection methodology including land use classes of choice. The SVM can be extended to handle several classes but then another change variable than change magnitude will have to be used.

- Possibility to add data with other spectral resolution such as mid infrared or thermal bands would make it possible to investigate other indices (for urban change detection) found in the literature that was not possible to utilize in this analysis.
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